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ACCURACY ASSESSMENT COMPARISON OF PER-PIXEL SUPERVISED AND OBJECT-ORIENTED LAND-COVER CLASSIFICATIONS ON A QUICKBIRD IMAGE

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Keywords: *Land-cover; QuickBird image; Per-pixel supervised classification; Object-oriented classification; Feature Analyst 4.2.*

Abstract: *Accuracy assessment comparison of 1) per-pixel supervised (in ERDAS Imagine software), and 2) object-oriented (in ArcGIS Feature Analyst 4.2. Extension tool) land-cover image classifications based on extraction of thematic information from very high resolution multi-spectral QuickBird image is presented in the present paper. The accuracy assessment comparison is applied on a highly fragmented urban and agricultural land, Novi Iskur District, Sofia municipality, Bulgaria, and includes several work stages. A land-cover classification scheme for the studied area was created. Large scale land-cover maps for the Novi Iskur District are composed based of the final results and the differences of each land-cover class are assessed using image analysis. The essential part of this study is using a combination of spectral reflectance and texture differences to extract different land-cover classes in the object-oriented classification. Unsupervised classification, fuzzy convolution filter, relief data, and Normalized Difference Vegetation Index (NDVI) were supplemented and used as ancillary data in the classification process. The Area of Interest (AOI) for both classifications is the same; this makes the comparison method possible. The accuracy assessment for both classifications was calculated using accuracy assessment tool in ERDAS Imagine software. It was found that the object-oriented classification has better overall classification accuracy (94.15%) than the per-pixel supervised classification (89.51%) and the overall Kappa statistics are respectively 0.9335 and 0.8776. Using an analysis tool in ArcGIS, the land-cover comparison was composed. Comparison matrix from per-pixel supervised to object-oriented classification is presented in the study. It can be concluded that the highest percentage of conversion has been detected regarding the land-cover class of Agricultural Land from the per-pixel supervised classification, which has been converted to Pastures and Orchards classes as high as 5%, compared to the object-oriented classification. This can be explained by the difficulty in separating Agricultural Land by using per-pixel type of classification, which involves mixed-pixel problem. The Orchards class has experienced about 4.50% of conversion to Forest Canopy and Pastures classes from per-pixel supervised to object-oriented classification. The Orchards class has that problem because it is very difficult to digitize accurate and pure AOI. One of the major problems includes the Transport and Industrial Infrastructure class which is converted to Residential Buildings and Agricultural Land classes in the object-oriented classification. This is a result, on one hand, from the mixed-pixel problem and, on the other hand, from the highly fragmented land which includes agricultural land in close proximity of the residential land which is difficult to assess by the per-pixel algorithm of image classification. Assessing the quality of the two basic image classification algorithms is important to evaluate the accuracy of each land-cover class. The study is useful for providing assessment of land-cover accuracy for both urban and non-urban environment.*

СРАВНИТЕЛНА ОЦЕНКА НА ТОЧНОСТТА МЕЖДУ ПИКСЕЛНО-ОРИЕНТИРАНА И ОБЕКТНО-ОРИЕНТИРАНА КЛАСИФИКАЦИЯ НА ЗЕМНОТО ПОКРИТИЕ ВЪРХУ САТЕЛИТНО ИЗОБРАЖЕНИЕ НА QUICKBIRD

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Ключови думи: *Земно покритие; пикселно-ориентирана класификация; обектно-ориентирана класификация; Feature Analyst 4.2.*

Абстракт: *В настоящият доклад е представена сравнителна оценка на точността между 1) пикселно-ориентирана (в ERDAS Imagine software) и 2) обектно-ориентирана (в ArcGIS Feature Analyst*

4.2. Extension tool), контролирана класификация на земното покритие, основана на извличане на тематична информация от изображение със свръхвисока пространствена разделителна способност от QuickBird. Сравнителната оценка на точността е извършена върху силно фрагментирана урбанизирана и земеделска територия, община Нови Искър, Столична голяма община, България и включва няколко работни етапа. Създадена е класификационна схема на земното покритие за изследваната територия. Съставени са едро-мащабни карти на земното покритие на основата на крайните резултати и разликите на всеки клас земно покритие е оценено използвайки методи за анализ на изображението. Ключово място в това изследване включва използването на спектралното отражение и текстурните различия за извличане на всеки клас земно покритие за обектно-ориентираната класификация. Като допълнение към класификационния процес са използвани: Неконтролирана класификация, Фъзи филтър, ЦМР (цифров модел на релефа) и Нормирания разликов вегетационен индекс(NDVI). Обучаващите множества за двете класификации са еднакви, поради което може коректно да се сравнят двете класификации. Оценката на точността беше изчислена за двете класификации използвайки инструмента за оценка на точността в ERDAS Imagine software. Беше установено, че обектно-ориентираната класификация има по-добра обща точност (94.15%) в сравнение с пикселно-ориентираната класификация (89.51%) и с Kappa статистика 0.9335 и 0.8776, респективно за двете. Използвайки analysis инструмента в ArcGIS сравнението на класовете земно-покритие беше извършено. Сравнителна матрица на изменението от пикселно-ориентираната към обектно-ориентираната класификация е представена в доклада. Може да се направи извода на базата на тази матрица, че най-висок процент на изменение се наблюдава при класа земно покритие Agricultural Land от пикселно-ориентираната класификация , като класа се изменя в класове Pastures и Orchards с около 5% в обектно-ориентираната класификация. Това може да се обясни с трудността при отделянето на класа Agricultural Land чрез използването на пикселно-ориентирана класификация, която е силно засегната от проблема със „смесеният пиксел” и съответно точността на класа земно покритие е по-малка. Класът земно покритие Orchards е подложен на около 4,50% изменение в класовете Forest Canopy и Pastures от пикселно-ориентираната класификация към обектно-ориентираната. Класа земно покритие Orchards е проблемен, защото е много сложно да се определи точно и чисто обучаващо множество без да има смесен клас в него. Един от основните проблеми при сравнителната оценка на точността включва класа Transport and Industrial Infrastructure, който е изменен в класовете Residential Buildings и Agricultural Land в обектно-ориентираната класификация. Това, от една страна, е резултат от проблема със „смесения пиксел”, а от друга - от силно фрагментираната територия, която включва земеделски ниви в близост до населените места, което прави класа труден за извличане чрез пикселно-ориентираната класификация. Сравнителната оценка на два основни алгоритъма за класификация на сателитни изображения е важно с оглед определяне точността на всеки индивидуален клас земно покритие. Докладът е полезен поради факта, че в него се оценява точността на класове земно покритие, както за урбанизираната, така и за неурбанизираната територия.

Introduction

Remote sensing has proved to be a powerful tool for monitoring rapid land-use changes. In the last three decades, the technologies and methods of remote sensing have dramatically progressed to include operating a suite of sensors at a wide range of platforms with potential interests and impacts on land planning and land management compared with the traditional manner [1]. Although the full potential of remote sensing technology for change detection applications has yet to be completely realized, planning agencies at local, regional and international levels now recognize the need for remote sensing information to help formulate policy and provide insight into future change patterns and trends [2]. Numerous researchers have addressed the problem of accurately monitoring land-cover and land-use change in a wide variety of environments with a high degree of success [3] [4] [5]. Further, the change-map product of two classifications often exhibits accuracies similar to the product of multiplying the accuracies of each individual classification [6] [7]. The major “mixed pixels” problem for accuracy assessment in the hard classifiers was solved by increasingly used fuzzy (soft) classifications [8].Various new techniques take into account, besides the spectral data, also the texture features of the image as additional layer in classification process [9]. An improved accuracy, especially for urban land-use/land-cover classifications, has been proposed by the object-oriented [10] and object-based [11] classifications.

The purpose of the present paper is to present accuracy assessment comparison of per-pixel supervised and object-oriented supervised land-cover image classifications using unsupervised classification, fuzzy convolution filter, relief data, texture analysis and Normalized Difference Vegetation Index (NDVI) as an ancillary data in the classification process. One of the major benefits of this study is that it is dealing with different kind of land-cover classes representing the non-urban environment like: Agricultural land, Natural Meadows, Pastures, Orchards, Water Bodies and Forest Canopy, as well as the urban environment: Transport and Industrial Infrastructure and Residential

Buildings, which is not a common practice. In order to achieve that several tasks have to be solved, which are explained below in section Results and Discussions.

1. Results and Discussions

The study has been applied on a highly fragmented urban and agricultural territory, district of Novi Iskur, municipality of Sofia, Bulgaria. The study area is 4.6067 square km. It includes several Work Stages described in details below.

1.1. Designing a geodatabase

A geodatabase was designed to store data from ground surveys, shape files, supervised and unsupervised classifications, photos and the chosen satellite image. A multi-spectral QuickBird image acquired on 31.05.2008 has been chosen. The chosen image is appropriate for image classification comparison because it is acquired when the agricultural land and forests are very well distinguished one from another. Additionally, a panchromatic image was used to increase the visual interpretation with its 0.61 meters spatial resolution compared with the 2.44 meters spatial resolution of the multi-spectral image. Digital Elevation Model (DEM) with 40-meter cell size and Rational Polynomial Coefficients (RPC) geometric correction model in ERDAS IMAGINE were used for orthorectifying the QuickBird image (from Digital Globe). Ground control points selected from orthophoto images with 0.5 meter resolution were used for adjusting the RPC values. The RPC model uses cubic polynomials for transformation from ground surface coordinates to image coordinates [12].

1.2. Creation of Classification Scheme and Assessing the Distribution of the /Land-cover Classes on the Territory Using the Information Gathered in the Geodatabase

A land-cover classification scheme for the studied area was created for both classifications using the information in the geodatabase including shape files, ground data and initial visual interpretation of the image. For that purpose, the first field check was conducted; ground control points (GCP) were taken with GPS receiver for some typical training sets for the studied land-cover classes; and test regions were evaluated for the both classifications from which to assess the accuracy of the classification.

Eight land-cover classes are recognized in the first level to be distributed in the studied area after the first field work: Transport and Industrial Infrastructure (TII), Residential Buildings (RB), Agricultural Lands (AL), Natural Meadows (NM), Orchards (O), Pastures (P), Forest Canopy (FC) and Water Bodies (WB). The second level of the classification scheme details these 8 land-cover classes to 11 land-cover classes as follows: Transport and Industrial Infrastructure, Residential Buildings, Crop 1 (C1), Crop 2 (C2), Crop 3 (C3), Natural Meadows, Orchards, Pastures, Coniferous Forest (CF), Deciduous Forest (DF) and Water Bodies.

1.3. Selection of a Method for Automatic Land-Cover Identification on the QuickBird Multi-Spectral Satellite Image

Automatic identification methods of the land-cover classes on the multi-spectral image were selected using visual interpretation and ground data gathered in previous stages of the work process. Four levels for automatic identification of the land-cover classes on the multi-spectral image were applied for the per-pixel supervised classification and three levels were applied for the object-oriented supervised classification. The training sets were digitalized using a visual interpretation of the image in different band combinations, as well as in-situ information from the ground surveys. Visual interpretation of the image was also used to identify the difference of the land-cover classes in hue, shape, size, structure, texture, shade, associations between them as the most common combinations of bands used were false color composite 4, 3 and 2 and true color 3, 2 and 1 as Red, Green and Blue, respectively.

1.4. Conducting Land-Cover Classifications and Evaluating their Accuracy

Four levels for automatic identification of the land-cover classes on the multi-spectral image were applied in ERDAS Imagine software for the per-pixel supervised classification and the following image processing procedures were used: 1) Normalized Difference Vegetation Index (NDVI) image and the information gathered in the geodatabase; 2) Unsupervised classification was conducted before the supervised classification of the image using the Iterative Self-Organizing Data Analysis Technique Algorithm (ISODATA). The unsupervised image was used to assess some differences in the agricultural land and the forest canopy, as additional layer from NDVI; 3) Supervised classification with non-parametric rule of parallelepiped and a parametric rule of maximum likelihood (MLC) was applied, and 4) Fuzzy convolution filter was used in order to reduce the mixed-pixel problem for the classified image.

Three levels for automatic identification of the land-cover classes on the multi-spectral image were applied in ArcGIS FEATURE ANALYST 4.2. tool extension for the object-oriented classification: 1) Normalized Difference Vegetation Index (NDVI); 2) Relief data (digital elevation model) with 10 meters cell size as elevation band data were used as an additional layer in the classification; and 3) Texture analysis. The selected band data were reflectance for the multi-spectral image and texture for the panchromatic image.

Normalized Difference Vegetation Index (NDVI) was used to digitalize properly the training sample for the classification process in both per-pixel supervised and object-oriented supervised classifications, especially for the class AL.

The confusion matrix provides the Overall Accuracy (OA) of the classification, which indicates the percentage of correctly classified pixels; the producer's accuracy (PA) and omission error indicate the probability that a classified pixel actually represents that category in reality; and the user's accuracy (UA) and commission error indicate how well training-set pixels were classified [13]. Two hundred (200) randomly distributed points on the image were used for calculating the accuracy assessment of the both resulted image classifications. Some of the points were positioned at the edge of the image, so these points were left out of the actual points from which accuracy was evaluated.

Table 1. Error Matrix Table for per-pixel supervised classification

Class Name	**C1**	**C2**	**C3**	**O**	**NM**	**P**	**CF**	**DF**	**RB**	**TII**	**WB**	**Row Total**
C1	19	0	0	0	0	0	0	0	0	0	0	19
C2	1	32	0	0	0	0	0	0	0	0	0	33
C3	0	0	2	1	0	0	0	0	0	0	0	3
O	0	0	0	26	1	1	3	1	0	0	0	32
NM	0	0	0	0	2	0	0	1	0	0	0	3
P	0	0	0	0	1	19	0	0	0	2	0	22
CF	0	0	0	0	0	0	12	0	0	0	0	12
DF	0	0	0	0	0	0	2	25	0	0	0	27
RB	0	0	0	0	0	0	0	0	3	3	0	6
TII	0	0	0	0	0	0	0	0	0	4	0	4
WB	0	0	0	0	0	0	0	0	0	0	1	1
Column Total	20	32	2	27	4	20	17	27	3	9	1	**162**

Table 2. Error Matrix Table for the object-oriented classification

Class Name	**C1**	**C2**	**C3**	**O**	**NM**	**P**	**CF**	**DF**	**RB**	**TII**	**WB**	**Row Total**
C1	12	0	0	0	0	0	0	0	0	0	0	12
C2	0	33	0	0	0	0	0	0	0	0	0	33
C3	0	0	33	0	0	0	0	0	0	0	0	33
O	0	0	0	20	0	0	1	5	0	0	0	26
NM	0	0	0	1	13	0	0	0	0	0	0	14
P	0	0	0	0	0	8	0	0	0	0	0	8
CF	0	0	0	0	0	0	8	0	0	0	0	8
DF	0	0	0	0	0	0	0	25	0	0	0	25
RB	0	0	0	0	0	0	0	0	7	1	0	8
TII	2	0	0	0	0	1	0	0	0	17	0	20
WB	0	0	0	0	0	0	0	0	0	0	1	1
Column Total	14	33	33	21	13	9	9	30	7	18	1	**188**

Table 3. Accuracy assessment comparison between per-pixel and object-oriented classifications

	Per-pixel supervised classification		Object-oriented classification	
Classes /Accuracy (%)	Producers	User's	Producers	User's
TI Infrastructure	44.44	100.00	83.33	83.33
Residential Buildings	100.00	50.00	100.00	87.50
Agricultural Land	98.33	87.88	95.23	100.00
Natural Meadows	50.00	66.67	100.00	92.86
Orchards	96.30	81.25	95.24	76.92
Pastures	95.00	86.36	88.89	100.00
Forest Canopy	81.59	96.29	86.11	100.00
Water Bodies	100.00	100.00	100.00	100.00

Therefore, the actual points used for the per-pixel and object-oriented classifications were 162 and 188, respectively. It was found that the object-oriented classification has better overall classification accuracy (94.15%) than the per-pixel supervised classification (89.51%), and the overall Kappa statistics was 0.9335 and 0.8776, respectively.

Considering the accuracy assessment table it can be concluded that TII, RB and NM classes are experiencing more difficulties in the per-pixel classification (with Producer's and/or User's accuracy below 70%) compared to the object-oriented classification. Good result is presented in the per-pixel classification regarding the class FC as a result from the additional processing applied like Fuzzy convolution and Majority filters and the preliminary experience with the unsupervised classification and NDVI image. For the object-oriented classification the classes P and FC are more difficult to assess, while the classes TII and RB are well presented and are having appropriate accuracy assessment considering the specifics of the territory studied.

1.5. Accomplishment of Visual Computer Aided Interpretation of the Classified Satellite Image

A Visual computer aided interpretation was performed for classes that have producers and users accuracy less than 80%. Based upon these conclusions some specific areas in the classified images were appointed for a field check in order to evaluate their difficulty in the classification process.

1.6. Conducting a Field Check of the Results

A field check of the results was conducted in order to compare the accomplished results from the accuracy assessment report with the actual situation on the field. The field work was accomplished throughout several visits to the studied area during 2009 and 2010 with the purpose to assess the agricultural land, forests and the urban environment. It was found that the RB class is more difficult to accurately be separated by spectral and even texture analysis because of the different roof-tops. The TII class, on the other hand, has even more complicated problem, because of the difficulty in recognizing the different ground surfaces or roofs of the industrial buildings as one single class in the classification process. The O class was also appointed for a field check as its accuracy in the object-oriented classification was below 80%. This can be explained with the difficulty in digitizing a good and representative training sample. The NM class showed very low accuracy (below 70%) for the per-pixel classification and the class was subjected of careful observations in the field check stage.

1.7. Composing a Large Scale Land-Cover Maps of the Two Supervised Classifications

A large scale land-cover maps were composed for the per-pixel supervised (Figure 1) and object-oriented supervised (Figure 2) classifications. The statistical method Majority from Focal statistic in ArcGIS 9.3 software was applied with the purpose of additional cleaning of the mixed pixels on the maps.

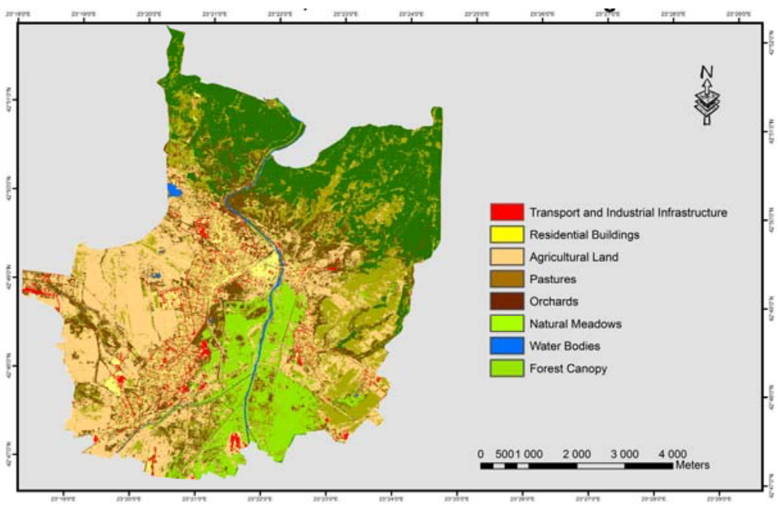

Fig. 1. Per-Pixel Supervised Classification of the District of Novi Iskur based on a QuickBird Image

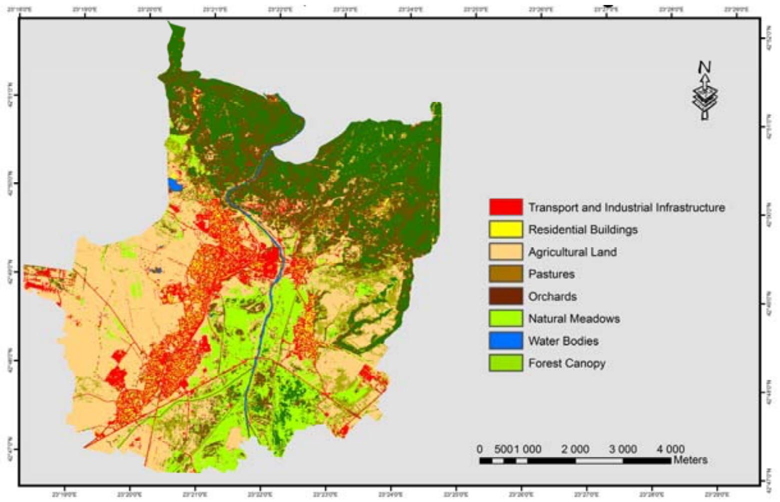

Fig. 2. Object-Oriented Supervised classification of the District of Novi Iskur based on a QuickBird Image

2. Accuracy assessment comparison of per-pixel supervised and object-oriented land-cover classifications

Using analysis tool in ArcGIS the accuracy assessment comparison of per-pixel supervised and object-oriented land-cover classifications was composed. It represents the land-cover classes' conversion between per-pixel supervised to object-oriented supervised classification. It shows the change in percentage from one to the other land-cover class using different image classification algorithms (Table 4).

The land-cover class Agricultural Land is experiencing conversions to land-cover classes Orchards and Pastures with 4.51% and 5.34% respectively. This is related with the spectral similarities between classes Crop 3 and Orchards which are quite difficult to discriminate using the unsupervised, per-pixel supervised and NDVI classified images. The Forest Canopy class is accurately classified in both classifications. This can be explained with the date of acquisition together with the good recognition between Coniferous forest and Deciduous forest by using false color composite. The Natural Meadows land-cover class is represented by 9.02% of the territory studied. There is an around 2% conversion to classes Orchards and Agricultural Land. This is also result from the spectral similarities of these land-cover classes. But considering the image processing procedures involved in the per-pixel supervised algorithm it is assumed that the Natural Meadows land-cover class has good result, which has reduced the error in a regular per-pixel supervised classification. The class Orchards is changed with around 4.50% to classes Forest Canopy and Pastures, which is a large number considering that the actual class Orchards represents only 6.35% of the studied territory. This is due to the difficulty in selecting appropriate training sample, the limited choice of training sample and the date of acquisition of the image. There were two approaches applied in digitizing this class: first to digitize only the crowns of the trees and the second to select the whole trees along side with inter-thins. The results from both approaches were unsatisfying. The land-cover class Pastures has little change from per-pixel supervised to object-oriented supervised classification. This is evidence for the precisely chosen training sample. The land-cover class Residential Buildings is also well classified which is also due to the carefully selecting training samples and not digitizing mixed classes as a learning algorithm for the classification. The land-cover class Transport and Industrial Infrastructure is class with low accuracy, which was investigated in the field work stage very carefully. After collecting all the evidence it can be concluded that this class is mixed with the land-cover class Agricultural Land. This is because these types of settlements are having gardens in the back yards of each house with different crops for family consummation. This makes them difficult to discriminate and the borders of the land-cover classes are experiencing mixed-pixel problems, which with different classification and image filters are difficult to solve. The land-cover class Water Bodies is accurately classified, which is based on the good spectral recognition of water by the two types of image classifications. Figure 3 shows summarized result from both supervised classifications. From that map it is evident that 59% are coinciding land-cover classes from both classifications and 49% are not coinciding. It can be concluded that the not coinciding land-cover classes are the Residential Buildings and Transport and Industrial Infrastructure land-cover classes, which proves the difficulty in discriminating these classes in the per-pixel supervised classification and also the difference in both algorithms despite the same training samples. The authors also recognize the complexity in dealing simultaneously with land-cover classes representing the urban and non-urban classes.

Table 4. Accuracy Assessment Comparison Table (in percentage %)

Class Name	Agricultural Land	Forest Canopy	Natural Meadows	Orchards	Pastures	Residential Buildings	Transport and Ind. Infrast.	Water Bodies	**Grand Totals**
Agricultural Land	20.97	0.01	1.97	0.56	0.99	0.99	3.30	0.00	**28.79**
Forest Canopy	0.00	14.50	0.00	4.26	0.02	0.01	0.02	0.01	**18.82**
Natural Meadows	0.23	1.29	9.02	0.39	0.00	0.00	0.03	0.00	**10.96**
Orchards	4.51	1.10	2.10	6.35	0.87	0.05	1.09	0.01	**16.09**
Pastures	5.34	1.07	0.50	4.50	4.05	0.31	1.31	0.00	**17.08**
Residential Buildings	0.42	0.01	0.01	0.02	0.00	1.40	2.61	0.02	**4.49**
Transport and Ind. Infrast.	0.27	0.00	0,00	0.00	0.00	0.50	2,36	0.00	**3.14**
Water bodies	0.01	0.03	0.00	0.09	0.00	0.00	0.02	0.48	**0.63**
Grand Totals	**31.75**	**18.00**	**13.60**	**16.18**	**5.94**	**3.27**	**10.74**	**0.53**	**100**

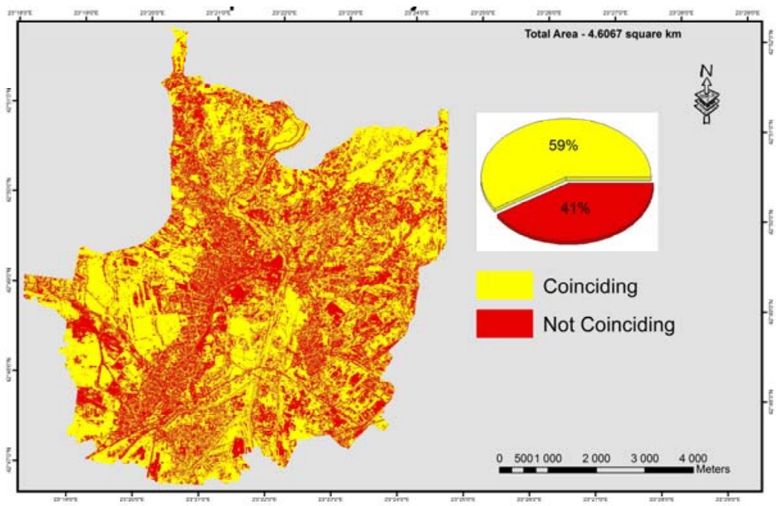

Fig. 3. Map of Coinciding and Not Coinciding Land-Cover Classes on Per-pixel Supervised and Object-Oriented Classifications on a QuickBird image

3. Conclusions

Considering the accuracy assessment tables for the both classifications it can be concluded that TII, RB and NM classes are experiencing more difficulties in the per-pixel classification (with Producer's and/or User's accuracy below 70%) compared to the object-oriented classification. Good result is presented in the per-pixel classification regarding the class FC as a result from the additional processing applied like Fuzzy convolution and Majority filters and the preliminary experience with the unsupervised classification and NDVI image. It can be concluded from that confusion matrix of the accuracy assessment comparison that the highest percentage of change has been detected regarding the land-cover class Agricultural Land from the per-pixel supervised classification, which has been changed to classes' Pastures and Orchards as high as 5% to the object-oriented classification. This can be explained with the difficulty in separating the Agricultural class by using per-pixel type of classification and the mixed-pixel problem. The class Orchards has experienced 4% of change compared to the per-pixel supervised classification and the conversions involve the Pastures and Forest Canopy land-cover classes. The class Orchard has significant problem because it is very difficult to digitize accurate and pure Area of Interest (AOI). Some other problems include the class Transport and Industrial Infrastructure which is changed from the per-pixel supervised classification to Residential Buildings and Agricultural Land classes in the object-oriented classification. As a future work the authors foresee the utilization of satellite images with better spectral resolution with the purpose of more accurate discrimination of land-cover classes with similar spectral properties and as a result giving better overall classification accuracy.

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